



Hill, PR., Bull, DR., & Canagarajah, CN. (2005). Image fusion using a new framework for complex wavelet transforms. In *IEEE International Conference on Image Processing 2005 (ICIP 2005) Genova, Italy* (Vol. 2, pp. II-1338 - II-1341). Institute of Electrical and Electronics Engineers (IEEE). <https://doi.org/10.1109/ICIP.2005.1530311>

Peer reviewed version

Link to published version (if available):  
[10.1109/ICIP.2005.1530311](https://doi.org/10.1109/ICIP.2005.1530311)

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# IMAGE FUSION USING A NEW FRAMEWORK FOR COMPLEX WAVELET TRANSFORMS

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## ABSTRACT

Image fusion is the process of extracting meaningful visual information from two or more images and combining them to form one fused image. Image fusion is important within many different image processing fields from remote sensing to medical applications. Previously, real valued wavelet transforms have been used for image fusion. Although this technique has provided improvements over more naive methods, this transform suffers from the shift variance and lack of directionality associated with its wavelet bases. These problems have been overcome by the use of a reversible and discrete complex wavelet transform (the Dual Tree Complex Wavelet Transform DT-CWT). However, the existing structure of this complex wavelet decomposition enforces a very strict choice of filters in order to achieve a necessary quarter shift in coefficient output. This paper therefore introduces an alternative structure to the DT-CWT that is more flexible in its potential choice of filters and can be implemented by the combination of four normally structured wavelet transforms. The use of these more common wavelet transforms enables this method to make use of existing optimised wavelet decomposition and re-composition methods, code and filter choice.

## 1. INTRODUCTION

Data fusion for images involves the combination of two or more images to form one image. The aim of such a fusion is to extract all the perceptually important features from all the original images and combine them to form a fused image in such a way that all the key features from each input image are still perceivable. The fusion of two or more images are often required for images captured using different instrument modalities or camera settings of the same scene or objects. Important applications of the fusion of images include medical imaging, microscopic imaging, remote sensing, computer vision, and robotics.

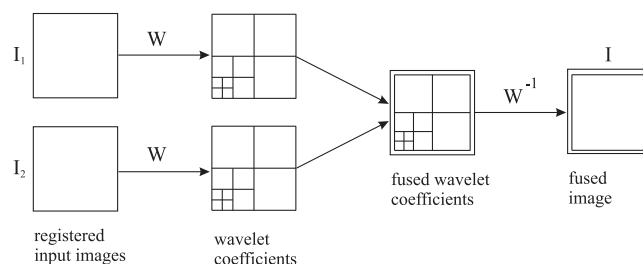
## 2. REAL VALUED WAVELET TRANSFORM FUSION

The most common form of transform image fusion is real valued wavelet transform fusion [1, 2, 3, 4]. As with all transform fusion techniques, all the input images are transformed and combined in the transform domain before an inverse transform results in the resultant fused image. The combination of the transformed images is achieved using a defined fusion rule. This rule can be as simple as choosing to retain the largest coefficient or more complicated windowed coefficient checks (see section 6).

The fusion of two images within the wavelet transform domain can be formally defined considering the wavelet transforms  $\omega$  of two registered input images  $I_1(x, y)$  and  $I_2(x, y)$  together with the fusion rule  $\phi$ . Then, the inverse wavelet transform  $\omega^{-1}$  is computed, and the fused image  $I(x, y)$  is reconstructed:

$$I(x, y) = \omega^{-1}(\phi(\omega(I_1(x, y)), \omega(I_2(x, y)))). \quad (1)$$

This process is depicted in figure 1<sup>1</sup>.



**Fig. 1.** Fusion of the wavelet transforms of two images.

## 3. COMPLEX VALUED WAVELET IMAGE FUSION

The use of the real valued wavelet transform for image fusion has given good results in the past especially when compared to naive pixel based and other transform methods such

<sup>1</sup> taken from [5]

as the Laplace pyramid [3]. However, the real valued wavelet transform suffers from shift variance and lack of directional selectivity. Nikolov *et al.* [5] introduced the use of the dual tree complex wavelet transform (DT-CWT) for image fusion. The DT-CWT is approximately shift invariant and has double the amount of directional selectivity compared to a real valued wavelet transform. Shift invariance is an important feature of a fusion transform as the magnitude of the coefficients of a shift variant transform may not properly reflect their importance. The improved directional selectivity of the DT-CWT is also important in order to properly reflect the content of the images across boundaries and other important directional features. The use of the DT-CWT for image fusion therefore gives considerable quantitative and qualitative improvements over the real valued wavelet transform as found by Nikolov *et al.* [5].

Figure 2 shows how two images are fused using a complex wavelet transform. As with the real valued case the transform coefficients of both images are combined using a simple fusion rule to give a combined transform. This is then inverse transformed to give the fused image. The fusion rule within this image is a simple choose maximum magnitude rule (see section 6). This figure also shows that the areas more in focus in the original images give rise to areas of higher magnitude in the subbands. This supports the use of the choose maximum fusion rule for the combination of such multifocus images.

Other fusion rules developed for the real valued wavelet transform [1, 2, 3, 4] can also be applied to the complex wavelet transform. However, the rules must be applied to the magnitude of the DT-CWT transform as the coefficients are complex valued.

#### 4. A COMPLEX WAVELET TRANSFORM USING PRE-PROJECTION

Decoupling the positive and negative directional components of each subband in a wavelet decomposition provides the improved direction selectivity of a complex wavelet transform. This is achieved by post-projection filters in the DT-CWT, where the first level filters are real and the subsequent filters project the remaining transform onto the complex two dimensional space. This can also be achieved in one dimension using the pre-projection complex wavelet transform [6] using two complex projection filters that attenuate positive and negative frequencies respectively at the first level of decomposition. A subsequent pair of real valued wavelet transforms produce subbands which retain either positive or negative frequencies from the frequency responses of the first level filters. In two dimensions this results in a similar directional decomposition to the DT-CWT as shown in figure 3. The complex filters from the first level are produced using the low pass filters of the subsequent levels'

low pass analysis filters  $H_0$ . This is achieved by shifting the frequency response of  $H_0$  by  $\pi/2$  in the positive and negative directions. e.g.  $H^+(z) = H_0(-jz)$  where  $H^+$  is the initial level complex filter that attenuates negative frequencies. The frequency response of such a filter is shown in figure 4. The converse filter  $H^-$  (i.e. attenuates positive frequencies) is similarly defined. Perfect reconstruction is possible as described by Fernandes *et al.* [6].

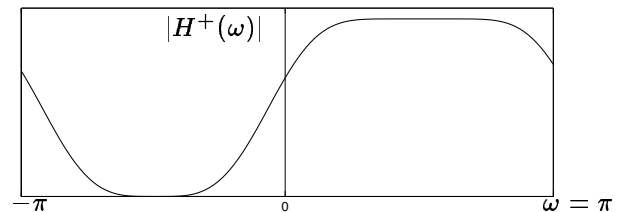


Fig. 4.  $|H^+(\omega)|$  absolute response of the mapping filter  $h^+$

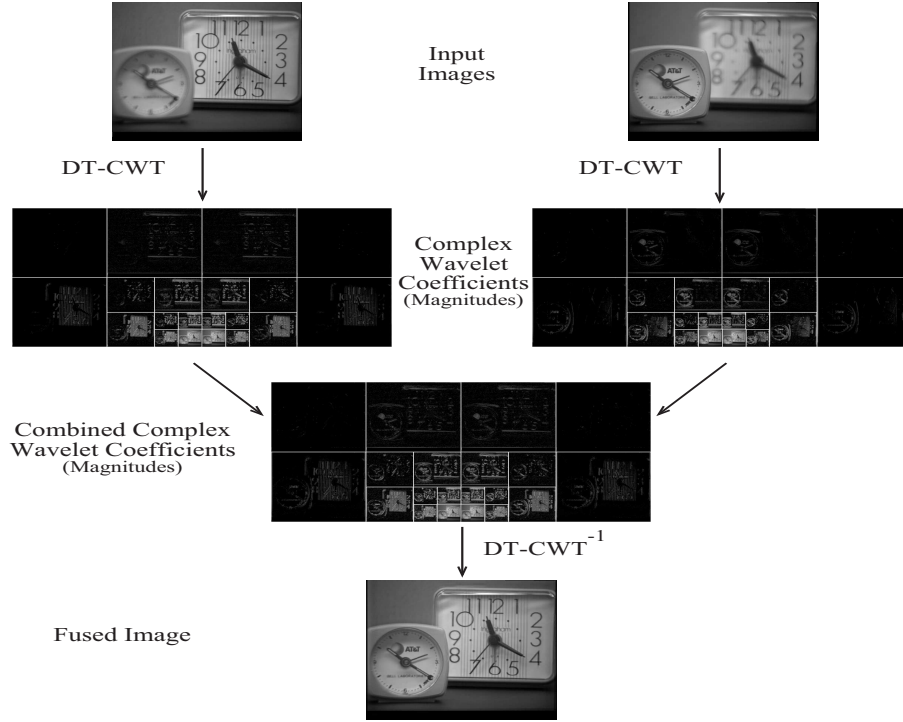
#### 5. IMAGE FUSION USING THE PRE-PROJECTION COMPLEX WAVELET TRANSFORM

The non-redundant complex wavelet transform shown in figure 3(a) did not give good results for image fusion. This was assumed to be from the reduced resolution of the decomposition bases. Therefore the redundant complex wavelet transform was used (figure 3(b)). The decomposition of the pre-projection complex wavelet transform produces exactly the same type and size of decomposition as the DT-CWT. Figure 2 therefore shows the fusion of two images using this new method with the pre-projection complex wavelet transform substituted for each DT-CWT transform.

#### 6. IMPLEMENTED FUSION RULES

Three previously developed fusion rule schemes were implemented using the pre-projection complex wavelet transform based image fusion:

- *maximum selection (MS) scheme*: This simple scheme just picks the coefficient in each subband with the largest magnitude;
- *weighted average (WA) scheme*: This scheme developed by Burt and Kolczynski [7] uses a normalised correlation between the two images' subbands over a small local area. The resultant coefficient for reconstruction is calculated from this measure via a weighted average of the two images' coefficients;
- *window based verification (WBV) scheme*: This scheme developed by Li *et al.* [1] creates a binary decision map to choose between each pair of coefficients using a majority filter.



**Fig. 2.** The image fusion process using the DT-CWT and two registered multifocus clock images.

## 7. EXPERIMENTAL FUSION METHOD COMPARISON

Evaluation of fusion methods is often very dependent on the intended application and therefore the features that need to be retained from each image. Many applications (such as medical image fusion or remote sensing fusion) require the fusion of perceptually important features such as edges or high contrast regions. Evaluation of fusion methods for such applications can only be made on the basis of a perceptual comparison. In other applications such as multifocus image fusion, computational measures can also be used for method comparison. The developed method is therefore compared with previous methods using both quantitative and qualitative comparisons.

### 7.1. QUALITATIVE COMPARISONS

The ringing artifacts noticeable within the real valued wavelet transforms are much less noticeable within the DT-CWT based fusion. This is also true of the pre-projection complex wavelet transform with no discernible difference between the two types of complex wavelet based fusion methods.

### 7.2. QUANTITATIVE COMPARISONS

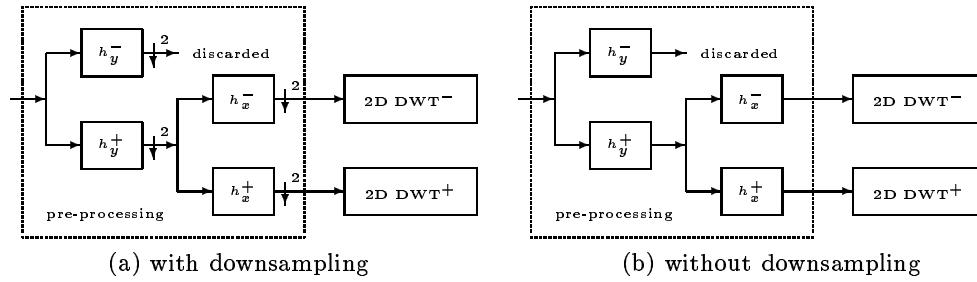
Often the perceptual quality of the resulting fused image is of prime importance. In these circumstances, comparisons

of quantitative quality can often be misleading or meaningless. However, a few authors [1, 8, 9] have attempted to generate such measures for applications where their meaning is clearer. Figure 2 reflects such an application: fusion of two images of differing focus to produce an image of maximum focus. Firstly, a “ground truth” image needs to be created that can be quantitatively compared to the fusion result images. This is produced using a simple cut-and-paste technique, physically taking the “in focus” areas from each image and combining them. The quantitative measure used to compare the cut-and-paste image to each fused image was taken from [1]

$$\rho = \sqrt{\frac{\sum_{i=1}^N \sum_{j=1}^N [I_{gt}(i, j) - I_{fd}(i, j)]^2}{N^2}}, \quad (2)$$

where  $I_{gt}$  is the cut-and-paste “ground truth” image,  $I_{fd}$  is the fused image and  $N$  is the size of the image. Lower values of  $\rho$  indicate greater similarity between the images  $I_{gt}$  and  $I_{fd}$  and therefore more successful fusion in terms of quantitatively measurable similarity.

Table 1 shows the results for the various methods used. The average pixel value method, the pixel based PCA and the DWT methods give poor results relatively to the others as expected. The DT-CWT methods give roughly equivalent results although the New-CWT method gave slightly worse results. The results were however very close and should not be taken as indicative as this is just one experiment and



**Fig. 3.** Analysis filter band structure for separable complex wavelet transform with pre-projection. (a) pre-projection with downsampling (no redundancy) (b) pre-projection without downsampling (4-1 redundancy)

the transforms are producing essentially the same subband forms. The WBV and WA methods performed better than MS with equivalent transforms as expected in most cases. The residual low pass images were fused using simple averaging and the window for the WA and WBV methods were all set to  $3 \times 3$ . The table 1 shows the best results for all filters available for each method.

Fusion Method	$\rho$
Average pixel fusion	7.7237
PCA (MS fusion rule)	7.7398
DWT (MS fusion rule)	6.1846
DT-CWT (MS fusion rule)	5.5528
New-CWT (MS fusion rule)	5.5730
DWT (WA fusion rule)	5.6821
DT-CWT (WA fusion rule)	5.7489
New-CWT (WA fusion rule)	5.5571
DWT (WBV fusion rule)	5.8770
DT-CWT (WBV fusion rule)	5.3862
New-CWT (WBV fusion rule)	5.3916

**Table 1.** Quantitative results for various fusion methods.

## 8. CONCLUSIONS

The introduced complex wavelet transform framework, the pre filter complex wavelet transform, produces equivalent fusion results to the dual tree complex wavelet transform (DT-CWT). However the DT-CWT suffers from a complex structure and constrained filter definitions. Not only is this new complex wavelet transform able to be implemented with an array of four conventional wavelet transforms, its more conventional design enables the more flexible selection of filters according to the nature of the application. Additionally, the use of commonly implemented wavelet transforms will enable the use of state of the art wavelet decomposition hardware and code, for speed and memory optimisation.

## 9. REFERENCES

- [1] H. Li, B.S. Manjunath, and S.K. Mitra, "Multisensor image fusion using the wavelet transform," *Graphical Models and Image Processing*, vol. 57, pp. 235–245, 1995.
- [2] L.J. Chipman, T.M. Orr, and L.N. Lewis, "Wavelets and image fusion," *IEEE Transactions on Image Processing*, vol. 3, pp. 248–251, 1995.
- [3] O. Rockinger, "Pixel-level fusion of image sequences using wavelet frames," in *Proceedings in Image Fusion and Shape Variability Techniques*, Mardia, K. V., Gill, C. A., and Dryden, I. L., Eds., pp. 149–154. Leeds University Press, Leeds, UK, 1996.
- [4] T.A. Wilson, S.K. Rogers, and L.R. Myers, "Perceptual based hyperspectral image fusion using multiresolution analysis," *Optical Engineering*, vol. 34, no. 11, pp. 3154–3164, 1995.
- [5] S. Nikolov, P.R. Hill, D.R. Bull, C.N. Canagarajah, "Wavelets for image fusion," in *Wavelets in Signal and Image Analysis, from Theory to Practice*, A. Petrosian and F. Meyer, Eds. Kluwer Academic Publishers, 2001.
- [6] F. Fernandes, *Directional, Shift-Insensitive, Complex Wavelet Transforms with Controllable Redundancy*, Ph.D. thesis, Houston, TX, August 2001.
- [7] P.J. Burt and R.J. Kolczynski, "Enhanced image capture through fusion," *Proceedings of the 4th International Conference on Computer Vision*, pp. 173–182, 1993.
- [8] O. Rockinger, "Image sequence fusion using a shift invariant wavelet transform," *IEEE Transactions on Image Processing*, vol. 3, pp. 288–291, 1997.
- [9] Z. Zhang and R. Blum, "A categorization of multiscale-decomposition-based image fusion schemes with a performance study for a digital camera application," *Proceedings of the IEEE*, pp. 1315–1328, August 1999.